Probabilistic short-term forecasts of Gulf of Alaska walleye pollock abundance and yield from an age-structured assessment model and multiple pre-recruit surveys

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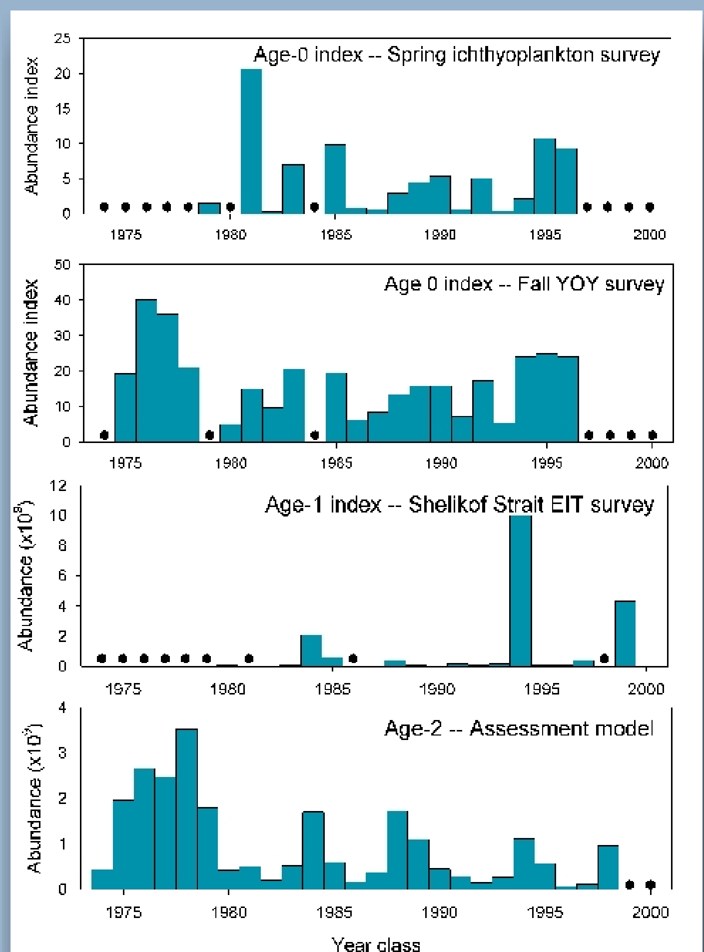


Figure 1. Comparison of pre-recruit indices of Gulf of Alaska walleye pollock with assessment model estimates of year-class abundance.

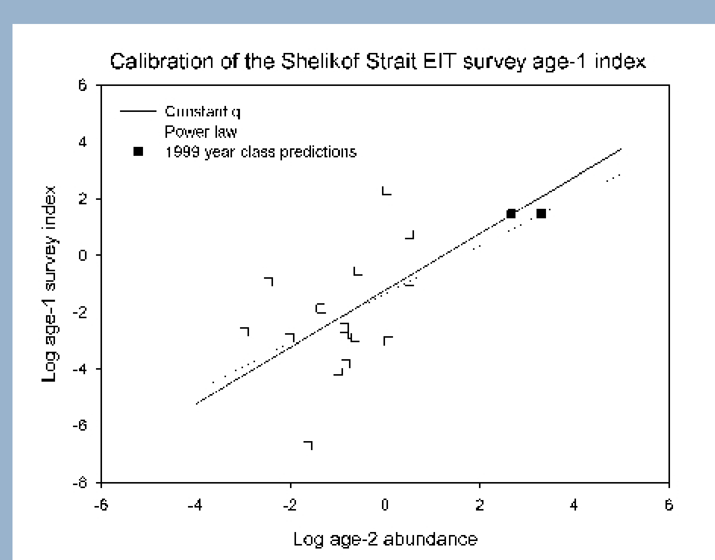


Figure 2. Calibration of the Shelikof Strait EIT survey age-1 index.

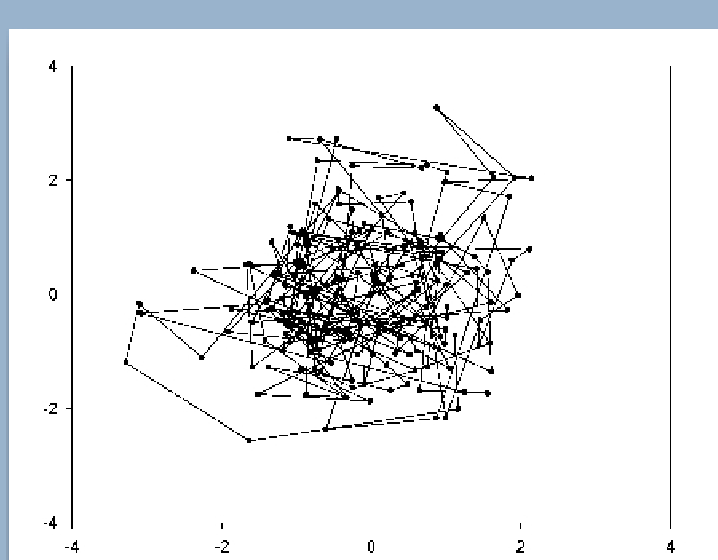
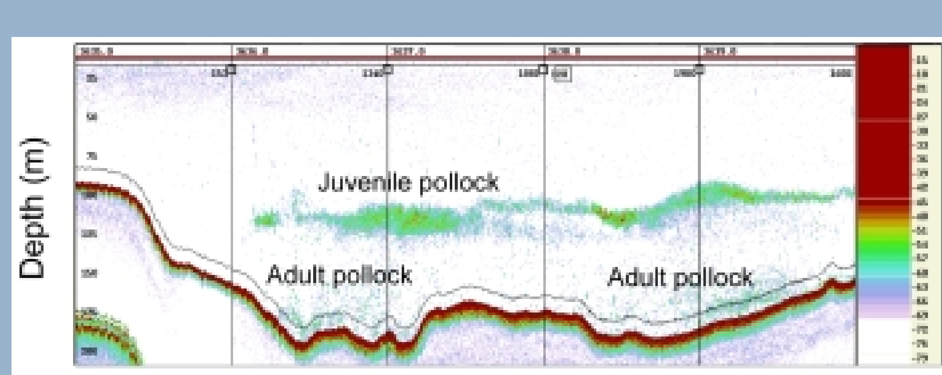


Figure 3. 500 MCMC samples from a bivariate normal distribution.



Introduction

When marine fish stocks are assessed on annual cycle, data from the previous year and earlier are used to provide harvest advice in the following year. As a result, there is typically a two-year lag between information and action. Since year-class strength for many fish stocks is highly variable, forecasts may depend strongly on incoming year-class. Pre-recruit surveys have the potential to "fill the gap" between fishery and survey information and the short-term forecast upon which management decisions are based.

The following elements need to be considered in this forecasting problem: (1) the current estimate of stock abundance (and its precision), (2) pre-recruit surveys that occur at different life stages (and their measurement errors), (3) the intrinsic variability in recruitment.

We have developed an approach that propagates abundance at age and its uncertainty forward in time. Pre-recruit surveys are calibrated in the assessment model and folded into population projections using inverse-variance weighting. We use Markov chain Monte Carlo (MCMC) sampling of the likelihood to obtain probability distributions of projected abundance and yield. We apply the method to Gulf of Alaska walleye pollock, a stock that has been studied intensively by NOAA's Fisheries Oceanography Coordinated Investigation (FOCI) program.

Survey Calibration

We used a statistical age-structured model with standard formulations for mortality and catch. The model was fit to time series of catch biomass, survey indices, and age and length composition. Model parameters were estimated by maximizing the log likelihood.

For a survey that produces an index of recruitment, predicted values are

$$\hat{R}_i = q_1 N_{i2}^{q_2}$$

Log-normal error in the survey index gives a log-likelihood of

$$\log L_k = \sum_i [\log(R_i) \quad \log \; q_1 - q_2 \log(N_{i2})]^2 / 2 \quad ^2$$

We evaluated an age-0 index from an ichthyoplankton survey in spring, an age-0 index from a young-of-year trawl survey in fall, and an age-1 index from a winter echo-integration trawl survey in Shelikof Strait.

Recruitment Projections

Recruitment predictions should account for two sources of variability: random variation in recruitment (process error) and sampling variability of the index (measurement error). For example, if recruitment itself is not highly variable, an index that shows an extremely low or high value should be shrunk towards the mean, particularly if the sampling variability is large. The tradeoff between these different sources of uncertainty is obtained by adding a log likelihood term for future recruitments.

$$\log L_{Fut.Recr.} = \frac{1}{2 \quad _r^2} \sum_i [\overline{\log(N_2)} \quad \log(N_{i2})]^2$$

$$\sum_k \frac{1}{2 \quad _k^2} \sum_i [\log(R_i) - \log(q_{k1}) \quad q_{k2} \log(N_{i2})]^2$$

The effect of this likelihood component is to obtain a recruitment prediction that is an inverse-variance weighted average of mean log recruitment and the log index.

What is Markov Chain Monte Carlo?

The MCMC algorithm generates a Markov chain of random samples (i.e., each sample is conditionally dependent on the preceding sample) whose stationary distribution is the likelihood function. The basic steps of the algorithm are: 1) draw an initial sample from the likelihood; 2) generate a candidate for the next sample using a random jumping distribution; 3) calculate the importance ratio, r, from the value of the likelihood at the current sample and the candidate sample; 4) if r is greater than one, accept the sample; 4) if r is less than one, accept or reject the candidate sample with probability r. 5) Begin the next cycle at step 2. Marginal likelihood distributions were obtained by subsampling every 200th sample from 1,000,000 cycles of the MCMC algorithm after an initial burn-in of 50,000 cycles.

Projection of Biomass and Harvest

The MCMC algorithm was used to make projections of walleye pollock biomass and yield. MCMC samples of dependent parameters and future recruitments are obtained using identical procedures. When a pre-recruit index is available, it is used to improve the recruitment prediction for that year. Otherwise recruitment is a MCMC sample from the log-normal recruitment likelihood. Marginal likelihoods are obtained from the MCMC samples using a kernel density estimator.

Conclusions

We have demonstrated the feasibility of using the MCMC algorithm to estimate the uncertainty of projections of biomass and yield. The use of the MCMC algorithm in likelihood-based statistical assessment models has many advantages. It is robust, easy to implement, and provides a general framework for assessing uncertainty. There appear to be no technical obstacles to incorporating other correlates of recruitment, such as environmental indices and time series effects, although uncertainty in the proposed relationship. Future work with this modeling framework is expected to focus on this problem as well as including Bayes priors for critical assessment parameters, such as natural mortality and survey catchability.

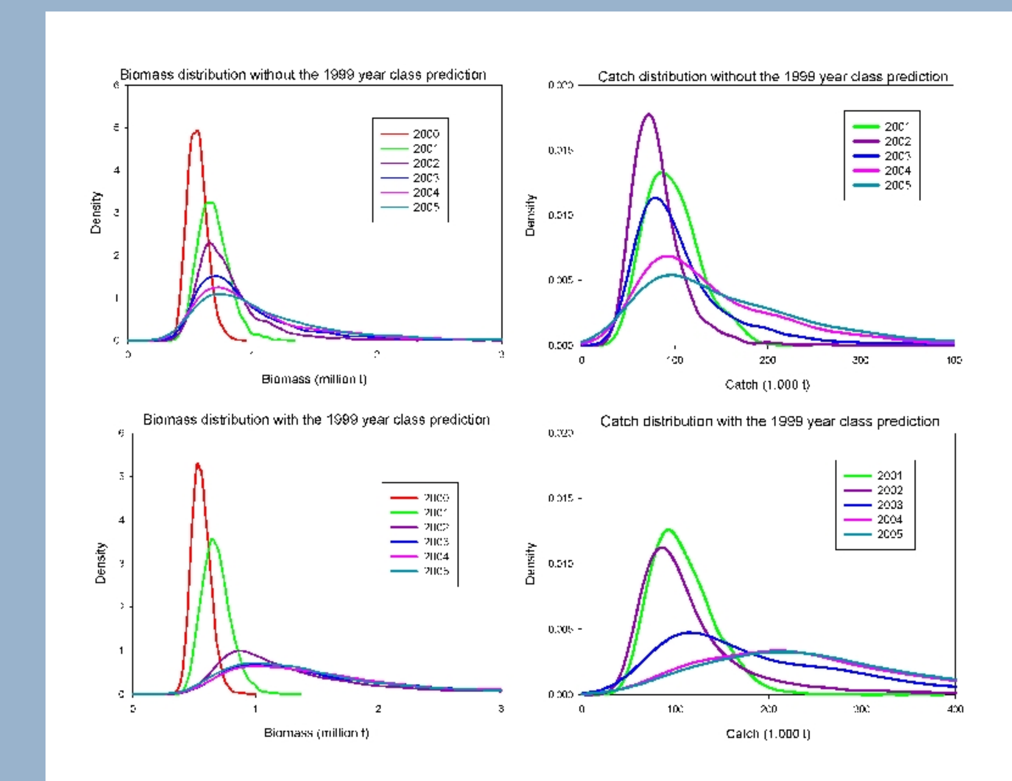


Figure 4. Projections of Gulf of Alaska walleye pollock biomass and catch under an F40% harvest control rule.

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